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Facilitating Consumers' Evaluation of Experience Goods and the Benefits for Vendors

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ABSTRACT

Despite the continuous growth of e-commerce, high levels of uncertainty about products and vendors may hinder this growth. Particularly online vendors of experience goods (such as media products) may face challenges to convince consumers, since the quality of their products is hard to assess prior to consumption. Additional guarantees (such as a money back guarantee) as well as easier access to product information may be used to reduce consumer uncertainty. However, these mechanisms are usually not for free.

By using experimental techniques and taking media products as an example, we analyze whether reductions in product uncertainty and search costs have an impact on consumer product search and purchase behavior. As an implication for praxis as well as research, we find that vendors can benefit significantly from employing these mechanisms in terms of search requests, purchases and consumer loyalty. Additionally, vendors may profit from consumers' uncertainty avoidance even if product uncertainty is low.

Keywords

E-commerce, consumer uncertainty, consumer product search, product quality uncertainty, search costs.

INTRODUCTION

Nearly all transactions bear uncertainty for consumers. For instance, vendors may fail to deliver the good or the delivered good may not be of the promised quality. In contrast to purchases in physical stores, when shopping online, products usually cannot be tried out prior to purchasing. This may result in higher consumer uncertainty levels, which may hamper e-commerce sales (Gefen 2000).

However, independent of their price, experience goods may be particularly affected by such high consumer uncertainty levels, because it is fairly difficult to assess their quality without consuming them (Shapiro and Varian 1999). On the other hand, depending on the product, after consumption, consumers may no longer benefit from holding the product and may not be willing to pay for it anymore. This holds true especially for certain types of media products (such as movies and news for instance). For example, many consumers watch most movies only once, and most news items are probably consumed only once by a person. Since media products are particularly affected by the aforementioned challenges and nowadays are frequently distributed over the Internet, they mark the focus of this paper.

There are several approaches to reducing product uncertainty of media products. One is the provision of free samples, to give consumers a better idea of the quality they can expect. Apple recently announced that it would extend, free of charge, the sample length of single tracks in its iTunes Store from 30 to 90 seconds, which is likely to further reduce consumer uncertainty concerning the product's quality. Many vendors also use recommender systems that collect, distribute, and aggregate feedback on products. Some large online retailers use extensive guarantees, not only to prove their credibility, but also to allow consumers a hassle-free return of the product in case they do not like it (Bailey 1998; Froomkin 1996).

However, challenges to evaluate the quality media products may also result from having difficulty finding a specific product or finding appropriate information on it. Therefore, providing more accurate or more convincing information than competitors do may result in lower search costs for consumers. For example, most online vendors nowadays implement consumer reviews. However, some may lack credibility due to a comparably small number of reviews.

Nevertheless, most of these mechanisms have an associated cost for vendors, i.e. for creating and operating a service (e.g. for a recommender system), or in the form of lower margins or missing out on sales (e.g. if consumers read a book once, then returns it within the money back guarantee).

Therefore, the main question for vendors is whether reducing consumer uncertainty has a positive effect on sales or whether consumers rather buy "ambiguously"? In this paper, we seek to contribute to a deeper understanding of consumer behavior. We address the following research questions:

(1.) What is the impact of a full coverage of consumer product uncertainty on consumer product search and purchase behavior?

(2.) How do consumers respond to reduced search costs in addition to reduced product uncertainty?

We therefore combine questions related to the reduction of product uncertainty with an easier access to products. We hold that a reduction in product uncertainty leads to higher vendor popularity (in terms of search requests, purchases, and consumer loyalty), especially when product uncertainty is high. We also hold that vendors can amplify these effects if they manage to reduce the search costs of consumers (for instance with consumer decision support systems), which in turn will result in higher consumer loyalty. However, we do believe that both factors – reduced product uncertainty and reduced search costs – are not necessarily entangled together. For instance, a money back guarantee for all products of an online shop does still not help consumers to identify the products they like most. On the other hand, a good product search engine can still leave consumers with substantial uncertainty concerning product quality, since finding the product consumers were looking for does not guarantee that it meets the consumers' quality expectations.

We used a laboratory experiment to examine the potential influence of uncertainty as well as search cost reduction. A laboratory experiment seemed suitable as it allowed us to control the exact influence of impact parameters, and to design a decision-making environment in which potential influencing factors can be evaluated unequivocally.

The remainder of the paper is organized as follows. We begin by introducing conceptual foundations. We then present our research model and develop our hypotheses on the relationships between the different impact factors and consumer behavior. We present the study's concrete implementation and research methodology, and subsequently report our results. After discussing our findings, we highlight implications for both research and practice and point out promising areas for future research.

RELATED LITERATURE

Information Asymmetry and Uncertainty in E-commerce

The impact of information asymmetry on various kinds of commercial markets has received considerable attention in both the economics and the information systems literatures and is closely related to uncertainty. Uncertainty is used in various ways in different research fields; it constitutes the "difference between information possessed and information required to complete a task" (Tushman and Nadler 1978). Information asymmetry arises since only the vendor (but not the consumer) is fully aware of the quality of the good. Uncertainty in vendor-consumer transactions is therefore the result of information asymmetries between the two parties. There are various other concepts of uncertainty, including behavioral, transactional, knowledge, and choice uncertainty (Pavlou, Liang and Xue 2007; Urbany, Dickson and Wilkie 1989). Overall, information asymmetries can cause single transactions or even markets to fail, as Akerlof illustrates with the market for "lemons" (Akerlof 1970).

Owing to the anonymity of the transaction partners, the ease of masquerading, and the challenges of inspecting products prior to a purchase, addressing information asymmetry and reducing uncertainty may be critical within e-commerce. As noted, there are several mechanisms for reducing information asymmetry; most are already known from traditional markets and are also applied in e-commerce. For instance, feedback mechanisms can serve as a signal and can increase consumers' trust in the vendor (Kim and Benbasat 2010; Pavlou and Gefen 2004). Trusted third parties facilitate transactions by assessing vendors and products and guaranteeing non-opportunistic behavior by market participants throughout the transaction (Clemons 2007; Kimery and McCord 2006). Brands and certificates are signaling mechanisms that may be used to indicate the quality of information (Kirmani and Rao 2000).

However, media products are experience goods. This means that consumers are usually unable to assess the quality of such a good ex ante, i.e. before consuming it. In the absence of clear information on the quality of the good it is therefore difficult for consumers to determine their own willingness to pay (Whinston, Stahl and Choi 1997). Excerpts and trial versions can also reduce consumer product uncertainty. Furthermore, in this context, recent technologies such as boards, virtual communities, and recommender systems seek to support consumers in assessing a good's value ex ante.

Consumer Product Search and E-commerce

Research on consumer search differentiates between classical normative search models, behavioral search models, and hybrid search models, whereas the current literature still provides conflicting findings on which model type provides the most appropriate approximations of de facto consumer search behavior (Häubl, Dellaert and Donkers 2010; Shu 2008; Stigler 1961; Zwick, Rapoport, Lo and Muthukrishnan 2003). Another fundamental distinction can be made between sequential and non-sequential search. Under sequential search, consumers evaluate one alternative after the other, i.e. after having seen the first product, they explicitly decide whether or not to continue searching for another product; each additional search step usually implies costs. Here, consumers face a trade-off between the potential benefit of additional searching (e.g. in the form of a lower price) and the additional costs associated with this search. They should therefore only perform an additional search step if the expected revenue resulting from to this search step is greater than the associated costs. Under non-sequential search, consumers decide only once, considering different alternatives simultaneously (Ratchford 1982; Weitzman 1979). Based on the search objective, research distinguishes between consumer product search and consumer information search. In the case of information search, consumers seek information on a specific product, while in product search, the nature of a particular product is not known to consumers prior to its inspection (Häubl et al. 2010).

In both offline and online consumer search, purchase decisions often involve searching for a desirable product from a number of relevant products. Consumers' primary motive for pre-purchase search is to enhance the quality of the purchase outcome (Punj and Staelin 1983). However, the Internet and accompanying new technologies (e.g. recommender systems) have a significant impact on the development of search costs. In comparison to brick-and-mortar environments, electronic markets help reduce the costs to consumers of collecting product information as well as the costs to the vendor of communicating such information (Bakos 1997). Electronic markets also allow for increased market transparency and reduced information asymmetry between the participants (Picot, Bortenlaenger and Roehrl 1995). Lower search costs can influence what consumers buy and also affect consumer welfare (De los Santos, Hortacsu and Wildenbeest 2011; Su 2008; Wu, Ray, Geng and Whinston 2004). In turn, consumer search efforts largely depend on the seeker's opportunity costs. While decreasing search costs are considered essential for improved market efficiency, they mostly imply a decreasing profit for the vendor. Although Internet technologies help reduce search costs and compare prices much faster than in brick-and-mortar environments, Internet shopping still requires significant time and effort from consumers (Brynjolfsson, Dick and Smith 2010; Hinz and Eckert 2010).

RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

As indicated in the economics literature, consumers prefer certain over uncertain outcomes (Fox and Tversky 1995). In line with this, media products are hard to evaluate prior to purchasing – even more so online; this may hinder sales. Therefore, online vendors may want to offer additional guarantees to reduce or prevent consumer uncertainty (Sha 2009). Given that consumers can buy the same products with or without uncertainty, uncertainty avoidance should lead consumers to buy from the vendor with the lower product uncertainty. If vendors include mechanisms that lead to the exclusion of product uncertainty, we hold that this will result in a competitive advantage for vendors as well as in higher consumer popularity. In praxis, such a mechanism could be a money back guarantee for the case that consumers are not satisfied with the product. We hold that such a mechanism creates a strong bond between the vendor and consumer, which pays off in terms of consumers using the vendor for information purposes, but also for final purchases. We therefore suggest that:

H1a: Vendors covering product uncertainty for media products have considerably more search requests from consumers than other vendors.

H1b: Vendors covering product uncertainty for media products have considerably more purchases from consumers than other vendors.

H1c: Vendors covering product uncertainty for media products benefit from a considerably higher consumer loyalty than other vendors.

Additional information on products may reduce uncertainty; if this occurs, additional value is created for consumers (Snow 2010). However, the vast increase of information in recent years and the huge assortment of products in some online shops constitute a challenge for consumers. Therefore, many online vendors have implemented decision support systems that seek to reduce consumer search costs (Chen, Shang and Kao 2009). Research has shown that search costs can have a significant impact on consumer decisions (Bakos 1997), although lower search costs do not necessarily lead to better purchase decisions (Diehl, Kornish and Lynch Jr 2003). However, if search costs are low, participants are better able to find a product that exceeds their reservation utility before search costs become too high. As a result, consumers should be more attracted to vendors that offer lower search costs. Therefore, we hold that lower search costs amplify the effects of reducing product uncertainty, leading to Hypotheses 2a-c:

H2a: A reduction in search costs leads to a further increase in search requests for vendors offering product uncertainty coverage.

H2b: A reduction in search costs leads to a further increase in purchases for vendors offering product uncertainty coverage.

H2c: A reduction in search costs leads to a further increase in consumer loyalty for vendors offering product uncertainty coverage.

According to prospect theory, people fear potential losses more than they appreciate equally large potential gains (Kahneman and Tversky 1979). Furthermore, we know that consumers tend to avoid uncertainty and that the extent of product uncertainty may differ across product types (Bock, Lee, Kuan and Kim 2012). In most cases, consumers may be unable to assess an objective level of uncertainty; concepts of perceived uncertainty therefore apply here (Pavlou et al. 2007). However, given that consumers avoid uncertainty (and keeping other factors constant), if consumers know how significant the uncertainty levels for various options are – they should choose the option with the lowest uncertainty. In this context, consumers should increase their usage of the uncertainty coverage if the product uncertainty is high; therefore:

H3a: The number of search requests for vendors offering product uncertainty coverage is considerably higher if product uncertainty is high.

H3b: The number of purchases for vendors offering product uncertainty coverage is considerably higher if product uncertainty is high.

H3c: Consumer loyalty for vendors offering product uncertainty coverage is considerably higher if product uncertainty is high.

Figure 1 presents an overview of our research model including the different hypotheses, market subjects, and measurements.

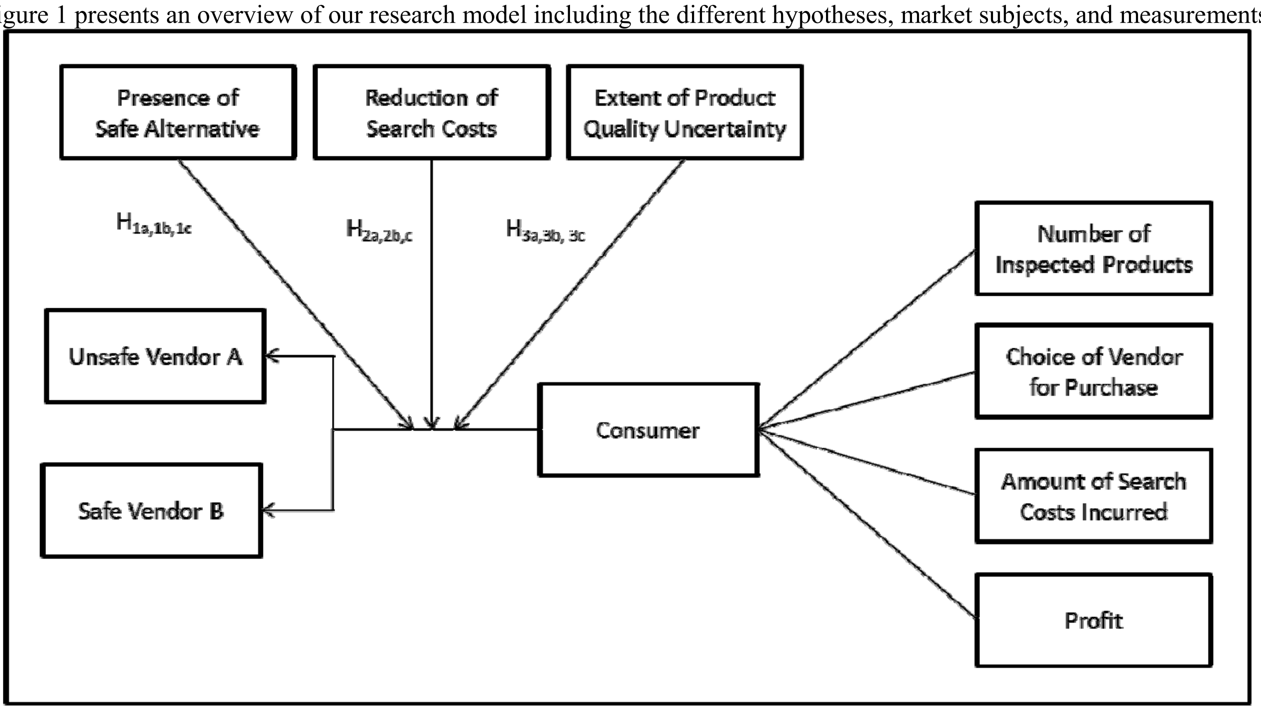

Figure 1. Conceptual Research Model

Experimental Layout

A total of 96 participants, mostly graduate and undergraduate students from various fields, were randomly assigned to two different groups, which differed in the level of the product uncertainty. The task comprised 15 rounds of 60 seconds each, which consisted of three different phases with five rounds each. The sessions lasted approximately 30 minutes. In order to prevent fatigue during the experiment, participants received interim information on their current payment. We ensured that participants understood the task, with elaborate instructions and sample screens providing a clear picture of the experiment, and one test round for each phase prior to the experiment itself.

Experimental Task

During each round, participants were asked to find one product that best fits their needs after deducting all costs necessary for finding the product. All participants' decisions were independent from the decisions of other participants. Participants could choose to buy either from Vendor A or Vendor B. Participants could inspect as many products as they wished and could freely switch between the two vendors. However, for each newly inspected product, they incurred a monetary cost representing search costs. On the other hand, participants could return to any previously inspected product without incurring any monetary costs, i.e. all products that had been inspected once remained accessible during that stage (recall function).

The participant's task was to maximize the difference between the utility of the purchased good and the total search costs incurred at that point. In accordance with random utility theory, a good's overall utility is a single value that integrates all attributes of a good including price (McFadden 1986).

Products offered by Vendor A ("unsafe vendor") differed from the products offered by Vendor B ("safe vendor") insofar as the products from the safe vendor inhibited uncertainty regarding the product quality, whereas products from Vendor B did not. Product uncertainty was mapped as a lottery-based variance factor that affects a product's utility, with the true utility being revealed to participants only after the purchase. Therefore, when inspecting products from Vendor A, participants saw two different utility values, each with a 50% chance of being drawn. However, as Vendor B covered product uncertainty, the utility of its products was revealed to participants right away.

Therefore, a specific utility was assigned to each product that was based on a uniform distribution and that ranged from 100 to 200 experimental units for the safe vendor, and from 100+/-x to 200+/-x experimental units for the unsafe vendor, with x being the product quality uncertainty factor.

Utilities for products i and j:

Unsafe Vendor A: $u_i = [100\text{-}x \ldots 200\text{+}x]$ Safe Vendor B: $u_j = [100 \ldots 200]$

To increase participant motivation, the payment depended on the participant's results. After each *round* $_k$, participants received the *payoff* y_k, which was calculated by subtracting the *search costs* c_k from the accumulated balance of the purchased good's *utility* u_k in each round. In other words, it was expected that participants would seek to maximize the difference between the purchased product's total utility minus all the search costs. The total payoff y is the sum of the pay-offs from all the single rounds:

Payoff after each round: $max \rightarrow \; y_k = u_k - c_k$

Total payoff: $y = \sum y_k$ while $y_k \geq 0$

Treatment Parameters

To allow for a clear isolation of the effects of product uncertainty coverage and search cost reduction, both impact factors were implemented on two levels. Concerning the first factor, there was no safe alternative during Phase I, leaving the participants to purchase only from the unsafe vendor. With regard to search costs, we accounted for significant search cost differences between various online vendors (Hinz and Eckert 2010). For instance, during Phase III the search costs of Vendor B were only 20% of the search costs of Vendor A.

To account for the influence of the extent of the product uncertainty, we also implemented two different levels, with a maximum standard deviation (in case of Group B), accounting for 20% of the average product utility. For Group A, uncertainty was significantly lower with a standard deviation of approximately 6.5% of the average product utility. The uncertainty factor for Group A was set to an amount equal to the search costs of the unsafe vendor. Table 1 summarizes the different treatment's primary characteristics.

Phase (Round)	Market Subjects		Search Costs		Product Quality Uncertainty	
	Vendor A	Vendor B	Vendor A	Vendor B	Group A	Group B
I (1-5)	Yes	No	10	-	10	30
II (6-10)	Yes	Yes	10	10	10	30
III (11-15)	Yes	Yes	10	2	10	30

Table 1. Parameter Values in the Different Phases

RESULTS

An overview of the results is provided in Table 2, which, for each of the three phases, reports the average values for the number of inspected products, the share of purchases made at each of the two vendors, the total search costs, and the resulting profit. The share of consecutive purchases per round at Vendors A and B is provided in Table 3. Based on this, we measured consumer loyalty as the share of two consecutive purchases at the same vendor within one phase.

The Kolmogorov-Smirnoff test as well as other graphical indicators show that most of the data do not follow a normal distribution; the following results are therefore based on non-parametric tests.

Phase / Group	Number of Inspected Products			Share of Purchases at		Search Costs	Profit
	Vendor A	Vendor B	Total	Vendor A	Vendor B	Total	Total
I / A	2,51	-	2,51	100%	-	25,13	154,13
II / A	0,88	1,67	2,55	38%	62%	25,50	153,37
III / A	0,16	3,98	4,14	3%	97%	9,57	177,35
I / B	2,20	-	2,20	100%	-	21,96	154,65
II / B	0,68	1,81	2,49	30%	70%	24,92	152,48
III / B	0,16	3,80	3,95	7%	93%	9,18	173,89

Table 2. Results of Search and Purchase Behavior in the Different Phases

To test the effects of the uncertainty coverage, the results of Phases I and II were compared as, in Phase I, participants were only allowed to purchase products from Vendor A. Whereas there were only slight and non-significant increases in the total number of searches for both groups (Groups A and B: p = < .001; two-sample Wilcoxon-Signed-Rank-Test; N = 96), Vendor B experienced a significantly higher number of search requests (Groups A and B: p = < .001; two-sample Wilcoxon-Signed-Rank-Test; N = 96), accounting for more than 50% of the purchases (Groups A and B: p = < .001; one-sample Wilcoxon-Signed-Rank-Test; N = 48). Furthermore, as indicated in Table 3, Vendor B had the largest number of consecutive purchases, thus indicating an increase in consumer loyalty (Groups A and B: p = < .001; two-sample Wilcoxon-Signed-Rank-Test; N = 96). It is worth noting that the provision of the uncertainty reduction led to slightly (but not significantly) higher search costs as well as decreasing profits. In sum, the offer of uncertainty reduction increased the popularity of the safe vendor in all cases, which led us to accept Hypotheses 1a-1c.

The additional search cost reduction was analyzed by comparing Phases II and III. There are significant increases in the total number of searches for both groups (Groups A and B: p = < .001; two-sample Wilcoxon-Signed-Rank-Test; N = 96). Compared to Phase II, Vendor B could furthermore significantly increase its number of absolute search requests as well as its number of relative search requests in comparison to Vendor A (Groups A and B: p = < .001; two-sample Wilcoxon-Signed-Rank-Test; N = 96). This was also true for the number of purchases from Vendor B (Groups A and B: p = < .001; two-sample Wilcoxon-Signed-Rank-Test; N = 96). Moreover, this was accompanied by a further increase in the number of loyal consumers, as indicated in Table 3 (Groups A and B: p = < .001; two-sample Wilcoxon-Signed-Rank-Test; N = 96). Owing to the search costs decrease for Vendor B, consumers incurred significantly less search costs and succeeded in increasing their profit (all differences in both groups were significant, with p < .001). This led us to accept Hypotheses 2a-2c.

Phase/Group \ Vendor	A->A	B->B	A->B	B->A
II / A	20%	45%	15%	19%
III / A	1%	94%	3%	3%
II / B	17%	57%	13%	14%
III / B	1%	88%	7%	4%

Table 3. Share of Consecutive Purchases per Round at the Different Vendors

To account for the influence of the extent of product uncertainty, differences between Groups A and B for Phases II and III were analyzed. The assumption was that higher product uncertainty is favorable for Vendor B. However, search requests for Vendors A and B differ only slightly between the groups for both phases, whereas, in Phase III, the safe vendor is used even less often in the high uncertainty scenario (Phase II: $p = .886$; Phase III: $p = .750$; two-sample Mann-Whitney-U-Test; $N = 96$). The same is true for the share of purchases from Vendor A (Phase II: $p = .188$; Phase III: $p = .124$; two-sample Mann-Whitney-U-Test; $N = 96$), and the share of loyal consumers (Phase II: $p = .119$; Phase III: $p = .125$; two-sample Mann-Whitney-U-Test; $N = 96$). This leads us to reject Hypotheses 3a, 3b, and 3c. Apparently, some consumers focus on whether or not the product quality evaluation is affected by uncertainty (even if the uncertainty is low), but not as much as on how large the uncertainty actually is, given that the mean expected product utility is not worse than the safe alternative.

CONCLUSIONS AND LIMITATIONS

In this paper, we sought to provide new insights into consumer behavior. We hope to contribute to both the theoretical body of knowledge and draw practical implications for online vendors, providing them with more information on whether or not the provision of additional services that seek to reduce product uncertainty and search costs when evaluating media products are appreciated by consumers.

Our study shows that vendors can benefit from offering additional services that remove consumers' product uncertainty and that they can considerably increase the number of search requests and purchases in their shops. Furthermore, consumers do not only use their shops more often; they are also more loyal repeatedly buy from these vendors. In addition, consumers highly value easier access to product information, which amplifies the aforementioned effects and thus, perhaps even allows for competitive advantages on the part of certain vendors. It may therefore be viable for vendors to invest in better shop designs and to offer consumers additional services. Depending on the cost of these courses of action, it seems worthwhile to offer these services in the form of optional utilities as they may result in a higher willingness to pay for certain types of consumers. For instance, uncertainty reduction as an additional option prior to the purchase (for instance in form of a money back guarantee) and search cost reductions in the form of an optional recommendation agent that can be selected at a surcharge. Furthermore, media products that are typically consumed more often (e.g. music) seem better suited for a money back guarantee than those that are usually consumed only once (e.g. news). Additionally, techniques that prevent further consumption if consumers return products need to be employed to prevent misuse.

It is also important to note that consumers seem to value a full exclusion of product uncertainty regardless of the extent of product uncertainty. This shows that many consumers do not wish to accept any uncertainty when buying media products online. As a result, vendors may successfully offer additional uncertainty reduction guarantees, even if product uncertainty is low. However, this circumstance may be dependent on other factors, such as product types, but also on how well consumers can estimate the actual product uncertainty. This limitation presents an opportunity for future research.

Despite our attempts to provide a comprehensive picture, the methodology we applied and a quest for simplicity limited the number of impact variables and levels, which required us to make certain assumptions. In order to avoid latent participant preferences, we did not use real vendor names or real websites. Nevertheless, consumers may tend to build relationships of trust with certain vendors and may therefore be more used to their websites, thus benefiting from lower search costs on specific sites. In contrast, they may also face lock-in effects that hinder them from easily switching to other vendors. Besides technical factors, there may be contractual aspects (such as subscription services) that constrict the consumers' choice of vendors.

In accordance with random utility theory, price was mapped as part of the overall product utility value. However, price may be an important factor in the consumer buying decision, which may also serve as a signal for product quality. A differentiation between price and the quality of the product is therefore an opportunity for future research. In order to isolate the effects in question, we assumed that both the uncertainty coverage as well as the search cost reductions were free to consumers. However, as noted, vendors may be charged a fee for these additional services, which could in turn be allocated to consumers. It therefore seems worthwhile to quantify how much consumers are willing to pay for both less uncertainty and easier access to products. We also suggest testing the validity of this study's findings in accordance with other market scenarios and product types.

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